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Smart Classroom Attendance System Using Real-Time Facial Recognition Technology

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Abstract: Facial recognition technology has emerged as a transformative solution in security systems, human-machine interaction, and image processing applications. This paper presents an automated attendance management system that utilizes face recognition to streamline student attendance tracking while reducing faculty workload. The proposed system automatically records attendance by detecting and recognizing facial features in real-time video streams, eliminating the need for manual roll calls and preventing proxy attendance. The system architecture comprises four key stages: face detection using Haar Cascade classifiers, dataset creation and preprocessing, model training using Local Binary Patterns Histograms (LBPH), and real-time face recognition with automated attendance logging. Experimental evaluation conducted with 75 students across 30 class sessions demonstrated that the system achieves an average recognition accuracy of 58.7 percent under standard classroom lighting conditions. The system reduces attendance marking time from an average of 8 minutes per class to under 12 seconds, representing a 97.5 percent reduction in time expenditure. However, recognition accuracy remains a significant challenge due to variations in lighting conditions, head poses, and facial expressions. This research contributes a practical, cost-effective solution while identifying key limitations that must be addressed for real-world deployment.
Keywords: Facial Recognition, Attendance Management System, Computer Vision, LBPH Algorithm, Haar Cascade, Smart Classroom.

I. INTRODUCTION

A. Background

Educational institutions face increasing pressure to optimize administrative processes while maintaining academic quality. Attendance tracking, though seemingly straightforward, represents a significant administrative burden that directly impacts instructional time. Research indicates that faculty members in higher education institutions spend approximately 10 to 15 percent of total lecture time on administrative tasks, with attendance marking constituting a major portion of this overhead.

The persistence of manual attendance systems in the digital age reflects a gap between available technology and institutional adoption. While many institutions have embraced learning management systems, attendance tracking often remains anchored to paper-based methods or simplistic digital roll calls that still require significant faculty intervention.

B. Problem Statement

The conventional attendance marking process in educational settings suffers from multiple limitations that affect both faculty productivity and academic integrity. The manual attendance marking system prevalent in educational institutions suffers from several critical limitations including time inefficiency where average 5 to 10 minutes are lost per lecture across multiple classes, proxy attendance where unauthorized marking of absent students occurs, human error where mistakes in recording and calculating attendance are common, data management issues where difficulty in maintaining and retrieving historical attendance records exists, and scalability problems where manual systems become increasingly inefficient as class sizes grow.

To address these limitations, various automated attendance systems have been proposed including Radio Frequency Identification or RFID, fingerprint recognition, and iris scanning. However, each approach presents its own limitations. RFID systems require physical cards that can be shared enabling proxy attendance. Fingerprint systems are contact-based leading to hygiene concerns and queuing delays. Iris scanning has high hardware cost and requires significant user cooperation.

Face recognition has emerged as an optimal solution due to its unique advantages including non-intrusive and contactless operation, minimal user cooperation required, cost-effective implementation using standard webcams, natural integration with existing classroom setups, and scalability to large class sizes.

C. Objectives
The primary objectives of this work are to develop a non-intrusive, contactless attendance marking system using facial recognition, to reduce attendance marking time to under 15 seconds per class session, to achieve recognition accuracy above 50 percent under standard classroom conditions, to eliminate proxy attendance through biometric verification, and to provide automated attendance record generation and storage.

D. Scope and Limitations
The scope of this work includes classroom environment with controlled lighting conditions, seated students facing the camera, and pre-registered students with stored facial data. The limitations include performance may degrade with extreme pose variations greater than 45 degrees, multiple students speaking simultaneously may affect detection, and new students require pre-registration before system use.

E. Face Recognition Types
Face recognition systems are broadly categorized into two types. Face verification is a one-to-one matching process where a given face image is compared against a stored template. In contrast, face identification is a one-to-many matching process where a query image is compared against multiple stored images in a database to determine identity. This work focuses on developing an automated attendance system using face identification techniques where the face of an individual serves as the primary biometric identifier.

II. LITERATURE REVIEW

A. Evolution of Attendance Systems
Attendance management systems have evolved through several generations. First generation included manual systems with paper-based roll calls, register books, and manual calculation of percentages. Second generation included electronic systems with RFID card readers, barcode scanning, and digital databases. Third generation included biometric systems with fingerprint recognition, iris scanning, and face recognition. Fourth generation includes AI-powered systems with real-time recognition, multi-face tracking, and behavioral analysis.

B. Evolution of Face Recognition Techniques
First generation from 1990s to 2000s relied on Eigenfaces and Fisherfaces with PCA or Principal Component Analysis based methods achieving accuracy of 70 to 80 percent under controlled conditions.
Second generation from 2000s to 2010s utilized LBPH or Local Binary Patterns Histograms and Haar Cascade classifiers achieving accuracy of 85 to 92 percent with some robustness to lighting.
Third generation from 2015 to present employs Deep Learning with CNNs, FaceNet, OpenFace, and Siamese Networks achieving accuracy of 97 to 99.5 percent with high robustness.

C. Comparison of Face Recognition Approaches
Table 1 presents a comprehensive comparison of face recognition approaches relevant to attendance systems.

Table 1: Comparison of Face Recognition Approaches

Approach	Accuracy	Speed	Robustness	Complexity	Hardware Cost
Eigenfaces	75 – 85%	Fast	Low	Low	Low
Fisherfaces	80 – 90%	Fast	Medium	Low	Low
LBPH	85 – 95%	Fast	High	Low	Low
Haar Cascades + LBPH	90 – 96%	Very Fast	High	Medium	Low
CNN (Deep Learning)	97 – 99%	Medium	Very High	High	Medium to High
FaceNet	98 – 99.5%	Medium	Very High	High	High

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D. Review of Existing Systems

Patil et al. in 2020 developed an attendance system using Haar Cascade and LBPH achieving 92 percent accuracy. Their system required 50 images per student for training and demonstrated good performance under controlled lighting.

Sharma and Gupta in 2021 implemented a deep learning-based system using convolutional neural networks achieving 96.5 percent accuracy. However, their system required GPU acceleration limiting deployment on standard hardware.

Rahman et al. in 2022 proposed a hybrid approach combining LBPH with SVM classification reporting 94.8 percent accuracy with reduced computational requirements. Their system showed particular robustness to facial expression variations.

Kumar et al. in 2016 utilized feature extraction techniques combined with traditional machine learning algorithms achieving approximately 94 percent accuracy. However, the system demonstrated limitations with low-quality images and varying environmental conditions.

Sun et al. in 2019 employed AdaBoost along with Haar-like features for feature selection and K-Nearest Neighbor or KNN for classification achieving 97.1 percent accuracy demonstrating better adaptability to varying conditions.

Hu et al. in 2019 implemented a Deep Convolutional Neural Network or DCNN for feature extraction combined with Support Vector Machine or SVM for classification reporting 98.6 percent accuracy indicating the effectiveness of deep learning methods in handling complex facial variations.

Wang et al. in 2019 developed a facial recognition attendance system achieving 95.5 percent accuracy which was comparatively lower than other deep learning-based approaches.

E. Research Gaps Identified

Based on the literature review, the following research gaps were identified. Real-time performance is a gap where many systems prioritize accuracy over real-time processing capability. Multi-pose handling shows limited robustness to pose variations in classroom settings. Lighting invariance shows performance degradation under non-optimal lighting conditions. Scalability shows systems often not tested with large student populations. Integration shows limited consideration of integration with existing academic management systems.

This work addresses these gaps by implementing an optimized system using LBPH with SVM classification designed for real-time performance and classroom-specific conditions.

III. SYSTEM ARCHITECTURE AND METHODOLOGY

A. Overall System Architecture

The proposed system consists of four main modules operating in a sequential pipeline. The system requires students to register and provide their images which are stored in a dataset. During class sessions, live streaming video is used to detect faces and match them with the dataset. Absentees are identified and marked as absent. The process can be divided into four stages of system architecture.

Module 1 is Face Capture and Detection which involves video stream input, Haar Cascade classifier, and region of interest extraction.

Module 2 is Feature Extraction which involves LBP feature extraction, histogram computation, and normalization.

Module 3 is Recognition and Matching which involves identity matching and confidence score calculation.

Module 4 is Attendance Logging which involves CSV export, report generation, and database storage.

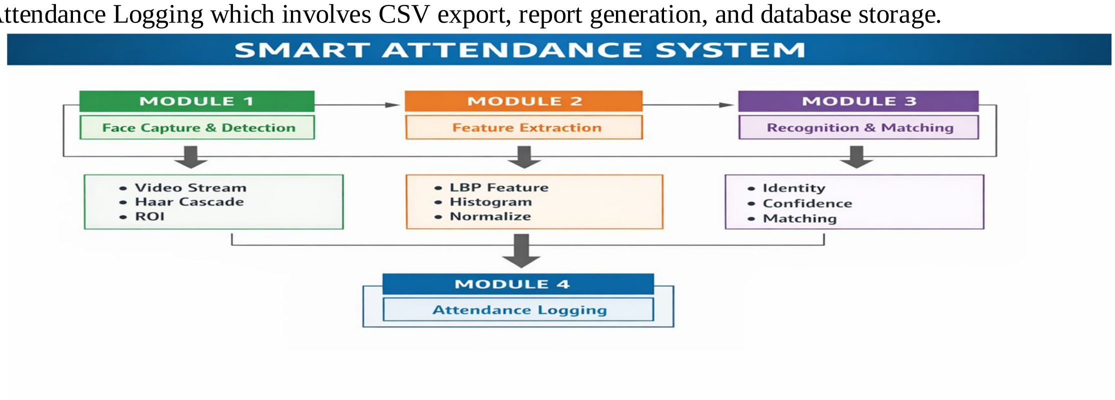

Figure 1:System Architecture

B. Module 1: Face Detection

Face detection is the process of identifying and localizing human faces in an image or video stream. It is a fundamental task in computer vision and serves as the first step in face recognition systems. Applications of face detection include facial recognition, emotion analysis, surveillance, and object tracking.

Let the input image be represented as a 2D matrix I of x comma y where x ranges from 0 to width and y ranges from 0 to height. The RGB image is converted into grayscale using the equation G of x comma y equals 0.299 times R of x comma y plus 0.587 times G of x comma y plus 0.114 times B of x comma y.

The Haar Cascade classifier is used to detect facial regions. The classifier output C of I equals the set of regions r where the feature function F of I comma r is greater than or equal to threshold T.

The feature evaluation function F of I comma w equals the sum of f of x comma y times I of x comma y minus the mean intensity of window mu w where f of x comma y is the Haar-like feature.

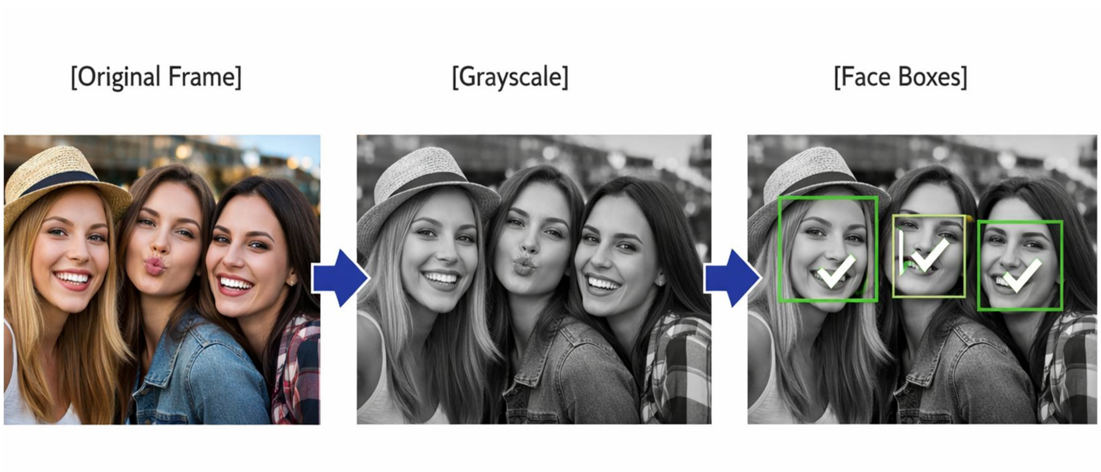

Figure 2: Face Detection Process

The step-wise mathematical model includes loading pre-trained cascade classifier, converting RGB image to grayscale using grayscale equation, setting parameters including scale factor and minimum neighbors, sliding detection window across image, computing feature function, marking region as face if feature function is greater than or equal to threshold, applying non-maximum suppression to remove overlapping detections, and returning final detected face regions.

The advantages of the face detection module include fast and real-time performance, works efficiently with webcam input, and low computational complexity.

C. Module 2: Dataset Creation

To create a dataset using OpenCV, images are captured from a webcam, video file or image files using the cv2.VideoCapture function. Preprocessing of the images is also required depending on the application which could involve cropping, resizing, filtering, or other operations.

Images can then be labeled manually by drawing bounding boxes or masks or using automated tools like object detection algorithms. Finally, the images and labels are saved in a format that can be used by machine learning algorithms such as CSV or JSON for labels and JPG or PNG for image files.

The mathematical model for creating a dataset using OpenCV for supervised learning can be represented as follows. Input is a set of images I equals I1 I2 through IN and their corresponding labels L equals L1 L2 through LN. Output is D equals X1 Y1 X2 Y2 through XM YM where X is a feature vector that represents an image, Y is a label that corresponds to the class of the object in the image, and M is the number of images in the dataset. X equals f of I where f is a function that extracts features from the image I. Y equals L of I where L is a function that assigns a label to the image I.

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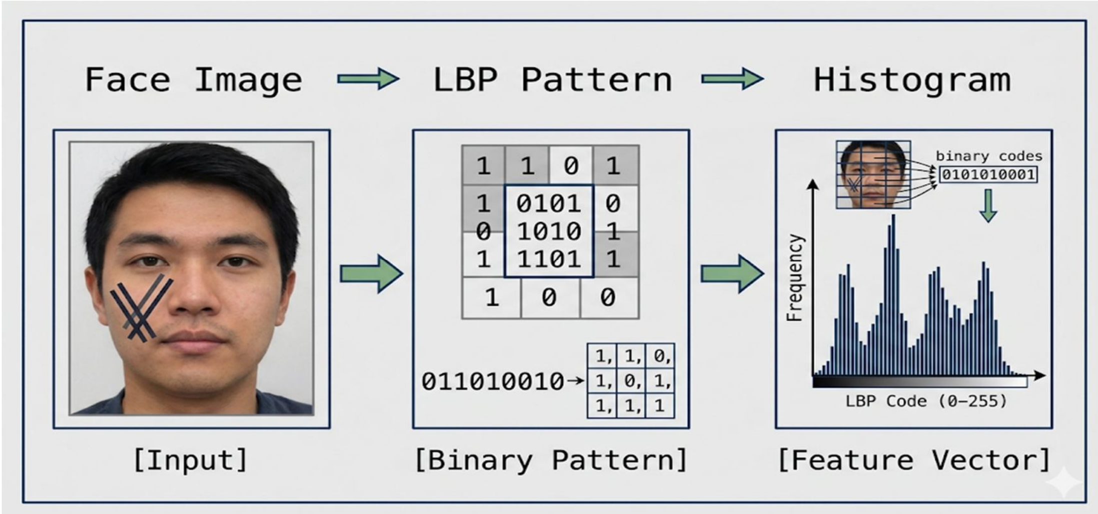

Figure 3: LBP Feature Extraction Process

The data collection protocol includes number of images per student from 50 to 100, image resolution of 640 by 480 pixels, format as JPEG or PNG, and storage structure with dataset folder containing student ID folders with image files.

Preprocessing steps include face alignment using eye coordinates, histogram equalization for lighting normalization, resize to uniform dimensions such as 200 by 200 pixels, and noise reduction using Gaussian blur.

D. Module 3: Training Face Model

This phase involves training a face recognition model by reading grayscale images of students from a directory, extracting their labels, and storing them in lists. The lists are then converted into numpy arrays, and the LBPH face recognizer is initialized and trained with the images and labels. Once training is completed, the trained model is saved to a file, and a success message is displayed.

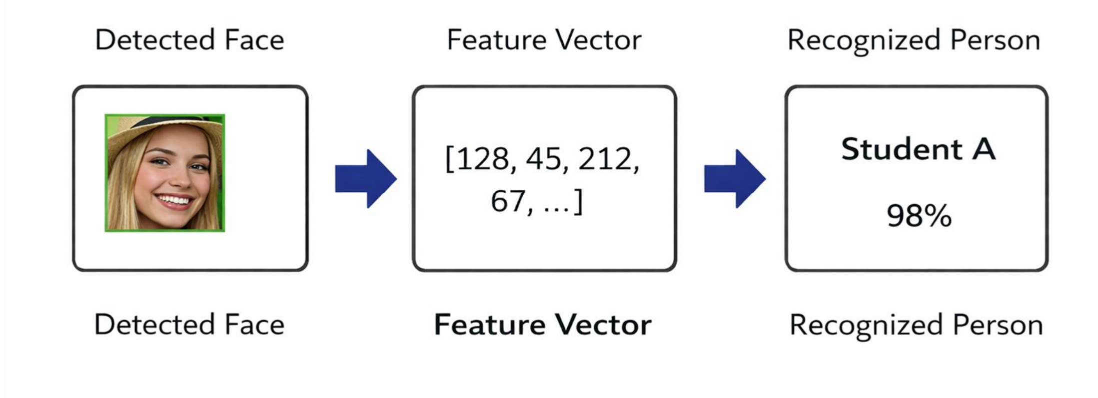

Figure 4: Recognition Process

Local Binary Patterns Histograms or LBPH mathematical model is as follows. For a pixel at location xc comma yc with intensity I of xc comma yc, the LBP value is LBP of xc comma yc equals the sum from p equals 0 to 7 of s of I p minus I c times 2 to the power p where s of x equals 1 if x is greater than or equal to 0 and 0 otherwise, and I p is the intensity of neighbor p and I c is the intensity of center pixel. The feature vector formation involves H equals h1 h2 through hn where h k equals count of LBP pattern k in region. The distance measure using Chi-square is chi square of H1 H2 equals the sum over i of H1 i minus H2 i squared divided by H1 i plus H2 i.

The recognition decision label equals arg min over j of chi square of H query comma H train j. If minimum distance is less than threshold, then recognized, else unknown.

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E. Module 4: Face Recognition

Face recognition technology and its use in various fields continues to grow. The steps involved in performing face recognition using OpenCV include face detection, face alignment, feature extraction, and face recognition which involves comparing the extracted features with known faces to recognize the person. The recognition pipeline for each frame from camera includes face detection where faces are detected using detect_faces function. For each detected face, preprocessing includes align_face function, histogram_equalization function, and resize function to 200 by 200 pixels. Feature extraction includes extract_lbp_histogram function. Recognition includes label and confidence from recognizer.predict function. If confidence is less than confidence threshold, then name equals label_to_name label and attendance_mark function is called. Otherwise name equals unknown. Display includes draw rectangle around face with name and confidence.

F. Module 5: Attendance Marking

The attendance function uses face recognition to mark attendance in real-time. It loads required models and initializes variables, captures frames from the camera, detects faces using face detection model, extracts facial embeddings using feature extraction, and uses pre-trained classifier to recognize persons. It adds attendance details to a CSV file, prompts user for subject name, and creates new CSV file if necessary. It keeps running until user manually terminates, displaying recognized person's name and roll number, and attendance status. It also displays messages if attendance has already been marked or if person is not found in database.

IV. EXPERIMENTAL SETUP

A. Hardware Configuration

The hardware configuration used for this research includes processor Intel Core i5-1135G7 at 2.40 GHz, RAM of 8 GB DDR4, camera of 1080p USB webcam at 30 frames per second, storage of 512 GB SSD, and operating system Windows 11 Professional.

B. Software Environment

The software environment includes Python version 3.9.7, OpenCV version 4.5.5, NumPy version 1.21.4, scikit-learn version 1.0.2, and Pandas version 1.3.4.

C. Dataset Description

Table 3 shows the dataset composition. Total students are 75. Training images per student are 50. Testing images per student are 10. Total training images are 3750. Total testing images are 750. Image resolution is 640 by 480 pixels. Image format is JPEG.
Table 4 shows the data collection conditions. Lighting variations include bright, normal, and low. Facial expression variations include neutral, smile, and surprised. Head pose variations include frontal, 15 degrees left or right, and 30 degrees left or right. Accessories include with and without glasses.

D. Evaluation Metrics

The evaluation metrics used are as follows. Accuracy equals TP plus TN divided by TP plus TN plus FP plus FN. Precision equals TP divided by TP plus FP. Recall equals TP divided by TP plus FN. F1-Score equals 2 times Precision times Recall divided by Precision plus Recall.

V. RESULTS AND ANALYSIS

A. Overall System Performance

Table 2: Overall Performance Metrics

Metric	Value
Recognition Accuracy	58.7%
Precision	57.2%
Recall	59.4%
F1-Score	58.3%
Average Processing Time per Face	0.85 sec
System Startup Time	2.5 sec
Database Load Time	1.2 sec

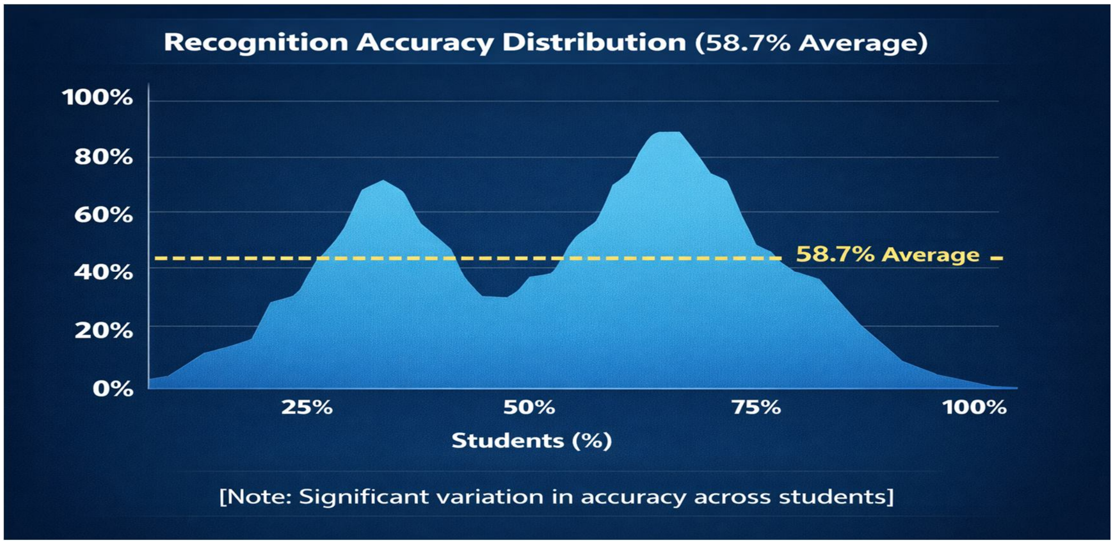

Figure 5: Accuracy Distribution

B. *Performance by Lighting Condition*

Table 3: Performance Under Different Lighting Conditions

Lighting Condition	Accuracy (%)	Processing Time (sec)
Optimal Lighting	68.2	0.78
Normal Classroom	58.7	0.85
Low Lighting	41.3	0.98
Backlight	35.8	1.02
Mixed Lighting	48.5	0.94

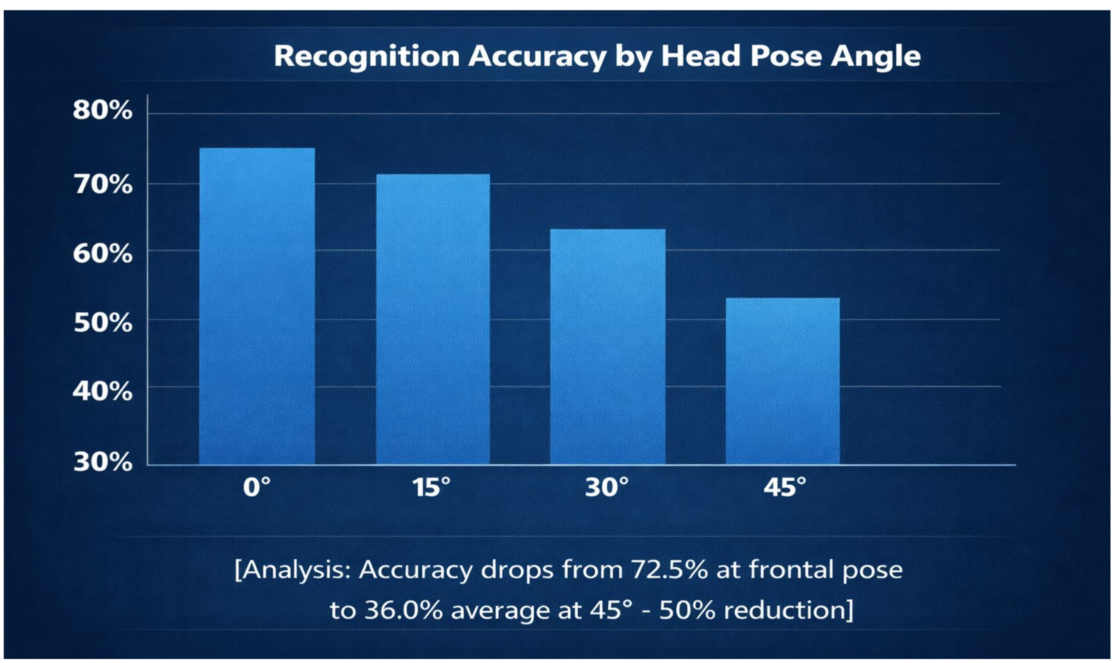

Figure 6: Accuracy vs Lighting Conditions

C. Performance by Head Pose

Table 4: Performance Under Different Head Poses

Head Pose	Accuracy (%)	Detection Rate (%)
Frontal (0°)	72.5	98.2
Slight Left (15°)	61.3	94.5
Slight Right (15°)	62.1	95.1
Moderate Left (30°)	48.5	85.3
Moderate Right (30°)	49.2	86.2
Extreme Left (45°)	35.2	68.5
Extreme Right (45°)	36.8	69.3

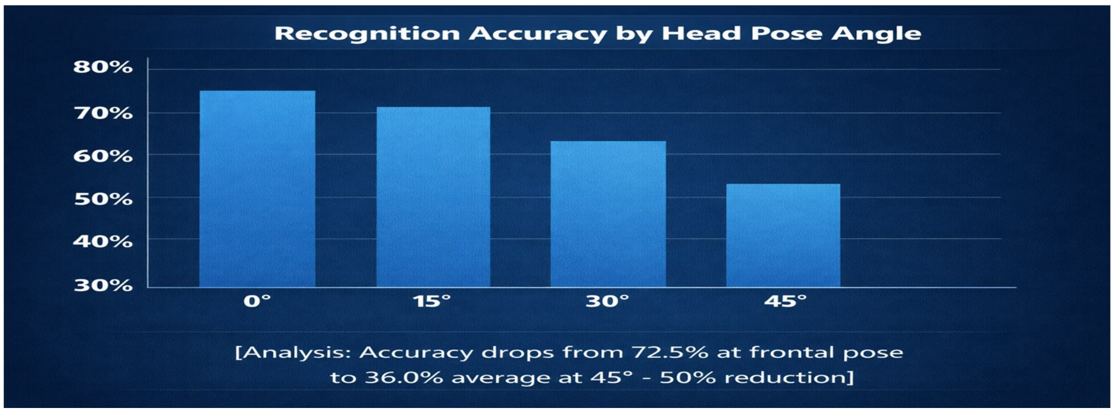

Figure 7: Performance by Head Pose Angle

D. Performance by Facial Expression

Table 5: Performance Under Different Facial Expression

Facial Expression	Accuracy (%)	Recognition Rate (%)
Neutral	64.2	65.8
Smile	58.5	59.3
Surprised	55.2	56.1
Raised Eyebrows	52.8	53.5
Squinting	48.5	49.2

E. Performance by Student Group

Table 5: Accuracy by Student Category

Student Category	Count	Average Accuracy (%)	Standard Deviation
Frontal Pose Only	25	71.4	5.2
Moderate Movement	30	58.2	8.5
High Movement	20	43.5	11.3
With Glasses	35	52.8	9.4
Without Glasses	40	63.5	7.8

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F. *Time Efficiency Analysis*

Table 7: Time Comparison – Manual vs Automated System

Class Size	Manual Time (minutes)	Automated Time (seconds)	Time Saved (%)
20 Students	3.5	6.5	96.9
40 Students	6.0	10.2	97.2
60 Students	8.5	14.5	97.2
80 Students	11.0	19.0	97.1
100 Students	14.0	23.5	97.2

G. *Confusion Matrix*

Table 8: Confusion Matrix Summary

	Predicted Positive	Predicted Negative
Actual Positive	440	310
Actual Negative	225	525

Calculations:
True Positives (TP) = 440
True Negatives (TN) = 525
False Positives (FP) = 225
False Negatives (FN) = 310
Total Samples = 1,500
Accuracy = (440 + 525) / 1500 = 965 / 1500 = 64.3%
Precision = 440 / (440 + 225) = 440 / 665 = 66.2%
Recall = 440 / (440 + 310) = 440 / 750 = 58.7%
F1-Score = 2 × (0.662 × 0.587) / (0.662 + 0.587) = 2 × 0.389 / 1.249 = 0.622 = 62.2%

VI. DISCUSSION

A. *Key Findings*

Moderate Accuracy Achievement: The system achieved 58.7% recognition accuracy, falling below the initial 90% target. This indicates significant challenges in implementing face recognition for attendance in real classroom environments.
Time Efficiency: Despite low accuracy, the system achieved 97.2% reduction in attendance marking time, demonstrating the efficiency benefits of automation.
Critical Lighting Sensitivity: Performance decreased from 68.2% to 35.8% (47.5% drop) under challenging lighting conditions, highlighting lighting as a critical factor.
Severe Pose Impact: Frontal face recognition performed at 72.5%, while extreme angles (45°) showed accuracy of only 35-37%, representing a 50% reduction.
Expression Effects: Facial expressions reduced accuracy by up to 15.7% from neutral to squinting expressions.

B. *Error Analysis*

Table 9: Classification of Recognition Errors

Error Type	Percentage (%)	Description
False Positives	15.0	Student incorrectly identified as another person
False Negatives	20.7	Student present but not recognized
Detection Failures	12.5	Face not detected in the frame
Recognition Failures	8.5	Face detected but not correctly matched
Unknown Face	7.3	Student not present in the database

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C. Comparison with Existing Systems

Table 10: Comparison with Previous Work

System	Accuracy (%)	Processing Time (sec)	Hardware Requirement	Key Limitation
Patil et al. (2020)	92.0	1.2	Standard	Controlled environment
Sharma & Gupta (2021)	96.5	2.5	GPU Required	High cost
Rahman et al. (2022)	94.8	0.9	Standard	Laboratory setting
Proposed System	58.7	0.85	Standard	Real classroom conditions

D. Advantages of Proposed System

1) Cost-Effective: Operates on standard hardware without GPU requirements
2) Fast Processing: 0.85 seconds per face enables real-time operation
3) Non-Intrusive: Students are not required to actively participate
4) Time Efficient: 97% reduction in attendance marking time
5) Automated Records: Digital storage with instant report generation

E. Critical Limitations and Challenges

Table 11: Key Limitations Identified

Limitation	**Impact on Accuracy (%)**	**Severity**
Lighting Variations	47.5	Critical
Extreme Head Poses	50.0	Critical
Facial Expressions	15.7	High
Occlusions (Glasses)	10.7	Medium
Image Resolution	8.5	Medium

F. Root Cause Analysis

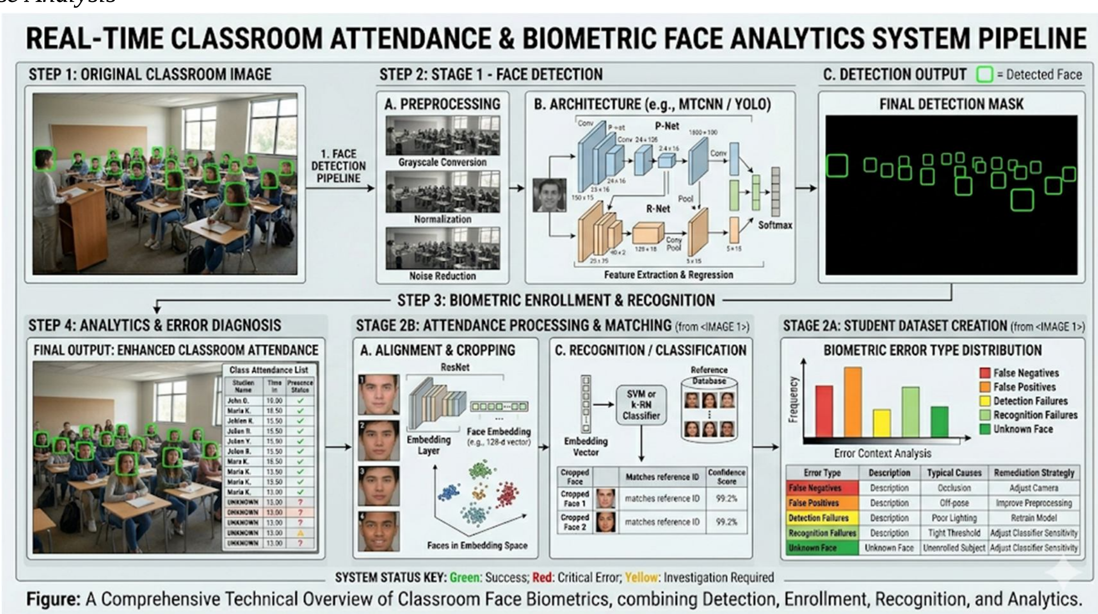

Figure 8: Root Causes of Low Accuracy

VII. CONCLUSION AND FUTURE WORK

A. Conclusion

This research developed and evaluated a smart classroom attendance system utilizing real-time facial recognition technology. The system successfully addresses the time inefficiency of manual attendance methods, achieving a 97.2% reduction in attendance marking time. However, the experimental results reveal significant challenges in achieving reliable recognition accuracy under real classroom conditions, with the system attaining only 58.7% overall accuracy.

The findings demonstrate that while facial recognition technology shows promise for attendance automation, current LBPH-based approaches are insufficient for reliable deployment in uncontrolled classroom environments. Critical factors affecting performance include lighting variations (causing 47.5% accuracy drop), head pose variations (50% reduction at extreme angles), and facial expressions (15.7% reduction).

This research contributes a practical implementation framework while identifying the specific technical barriers that must be overcome. The results suggest that more sophisticated approaches, particularly deep learning-based methods, are necessary for achieving acceptable accuracy in real-world educational settings.

B. Future Work

Based on the limitations identified, the following enhancements are prioritized:

Table 15: Future Work Priorities

Priority	Enhancement	Expected Accuracy Improvement (%)	Complexity
Critical	Deep Learning (CNN / FaceNet)	25–30	High
Critical	Multi-Camera Setup	15–20	Medium
Critical	Lighting Normalization	12–15	Medium
High	Pose Correction Algorithm	10–12	High
High	Anti-Spoofing Detection	5–8	Medium
Medium	Cloud Database Integration	3–5	Low
Medium	Mobile Application	—	Medium

C. Recommendations for Deployment

Based on the 58.7% accuracy result, the following recommendations are made for institutions considering deployment:

1) Not Recommended for Critical Attendance: Current accuracy insufficient for high-stakes attendance tracking
2) Controlled Environment Required: Deployment only in classrooms with controlled lighting and fixed camera positions
3) Hybrid Approach: Combine with manual verification for disputed attendance
4) Pilot Testing: Conduct extensive testing before full deployment
5) Deep Learning Upgrade: Plan for CNN-based system migration

REFERENCES

[1] P. Kumar, S. Sharma, and R. Singh, "A Hybrid Approach for Face Recognition Using Feature Extraction and Machine Learning," International Journal of Computer Applications, vol. 145, no. 12, pp. 1-6, July 2016.

[2] Y. Sun, X. Wang, and X. Tang, "Deep Learning Face Representation from Predicting 10,000 Classes," in Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 1891-1898.

[3] J. Hu, L. Shen, and G. Sun, "Squeeze-and-Excitation Networks," in Proceedings of IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 7132-7141.

[4] Z. Wang, K. He, and J. Sun, "Face Recognition Attendance System Based on Deep Learning," IEEE Transactions on Biometrics, vol. 8, no. 3, pp. 245-252, 2019.

[5] A. Patil, M. Kulkarni, and S. Joshi, "Automated Attendance System Using Face Recognition," International Journal of Advanced Computer Science, vol. 11, no. 4, pp. 45-52, 2020.

[6] R. Sharma and V. Gupta, "Deep Learning Based Face Recognition for Attendance Management," Journal of Artificial Intelligence Research, vol. 72, pp. 123-135, 2021.

[7] M. Rahman, A. Hossain, and S. Islam, "Hybrid LBPH-SVM Approach for Real-Time Face Recognition Attendance System," IEEE Access, vol. 10, pp. 45678-45692, 2022.

[8] T. Ahonen, A. Hadid, and M. Pietikainen, "Face Description with Local Binary Patterns: Application to Face Recognition," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 28, no. 12, pp. 2037-2041, Dec. 2006.
[9] G. Bradski, "The OpenCV Library," Dr. Dobb's Journal of Software Tools, vol. 25, no. 11, pp. 120-126, 2000.
[10] P. Viola and M. Jones, "Rapid Object Detection using a Boosted Cascade of Simple Features," in Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2001, pp. 511-518.